Factors regulating Shasta Lake (California) cold water accumulation, a resource for endangered salmon conservation

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[1] Shasta Lake, in northern California, has recently experienced reduced cold water storage, making it difficult to meet downstream temperature objectives for endangered winter-run chinook salmon spawning habitat. This study used a novel form of time series analysis to examine the causes, timing, and predictability of cold water storage in Shasta Lake. This analysis detected two independent modes of variability in Shasta Lake cold water storage. The first mode, representing variability during February–July and describing 64% of the overall variability in cold water storage, was negatively correlated with both the preceding year's late summer hypolimnetic discharges and that spring's air temperatures. A second mode, representing December–January and describing an additional 24% of variability, was negatively correlated with Shasta Lake fall water temperatures and winter air temperatures and positively correlated with winter inflows. These results suggest hypolimnetic discharges, air and water temperatures, and inflows act in concert to determine cold water storage in Shasta Lake. These results also suggest water column mixing should be promoted during the cold midwinter period and thermal stratification should be promoted the remainder of the year to minimize surface warming of the entire water column. *INDEX TERMS:* 1845 Hydrology: Limnology; 1857 Hydrology: Reservoirs (surface); 1884 Hydrology: Water supply; *KEYWORDS:* climate, cold water, hypolimnion, limnology, reservoir, Shasta Lake

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1. Introduction

[2] Shasta Lake is the largest and most important water supply reservoir for the agriculturally rich Central Valley of California. One of the greatest challenges to federal and state dam operators is managing the oftentimes competing interests of various users such as agriculture, urban areas, hydropower, flood protection, and, more recently, habitat protection for endangered and economically important fish. In some cases the difficulties inherent in balancing these interests have resulted in intense disputes between the various user groups and the federal agencies responsible for managing water resources and endangered species [*National Research Council*, 2002; *Levy*, 2003]. Since 1987, the Bureau of Reclamation (BOR) has been under a federal court order to provide suitable spawning habitat for endangered winter-run chinook salmon (*Oncorhynchus tshawytscha*) in the Sacramento River below Shasta and Keswick Dams [*National Marine Fisheries Service* (*NMFS*), 1987]. This court order, and the classification of winter-run chinook as first threatened and then endangered, was motivated by the fact that winter-run spawning returns declined from an average of ~90,000 fish annually during the late 1960s to ~2000 fish annually during the late 1980s and early 1990s. In response to the court order, the Central Valley Regional Water Quality Control Board adopted a late summer/fall discharge temperature objective of 13.3°C (56°F) for the 100 km river reach between Keswick Dam and Red Bluff, California [*Deas et al.*, 1997]. To compensate for intense solar and atmospheric heating during the summer, operators at Shasta Dam were forced by the court order to release cold water through a low-level dam outlet. The target release temperature from Shasta Lake is 8.3°C (47°F) from May through August [*Hanna et al.*, 1999]. The BOR must also release more cold water during especially warm summer periods because river heating is inversely proportional to river flow. Between 1987 and 1997, cold water was discharged through the lower outlet works, bypassing the power generating turbines, resulting in an approximate $63 million loss in hydropower generation during this period [*Vermeyen*, 2000]. To recapture this lost hydropower, the BOR installed an $80 million temperature control device (TCD) in 1997, which now directs all

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outflow through the penstock intake. Shutter gates on the TCD move vertically to selectively withdraw water from varying depths allowing for control of outflow temperature while still passing water through the power generating turbines.

[3] During most of the 1990s, large volumes of hypolimnetic water were discharged to maintain downstream temperatures. During this period, Shasta Lake also had some of the lowest recorded volumes of cold water storage preceding the periods when this cold water was needed for downstream temperature control [*Brett et al.*, 1998]. This reduced cold water accumulation often made it difficult for dam operators to meet the outflow temperature objectives in the late summer/fall and led authorities with the National Marine Fisheries Service (NMFS) to reduce the protected spawning reach to less than the desired 100 km. Some of this observed poor accumulation of cold water could have been due to droughts during the early 1990s. However, poor cold water accumulation during this time also raised concerns that the hypolimnetic bypass operations may have directly or indirectly impacted the ability of Shasta Lake to trap incoming cold water.

[4] The objectives of this study are twofold; first, to determine whether the observed poor cold water accumulation during the 1990s was due in some way to the concurrent hypolimnetic discharges. This is important because the court ordered hypolimnetic bypasses are in many respects similar to expected TCD impacts on the hydrology of Shasta Lake. The second, and more critical, objective is to develop a predictive model which elucidates the primary mechanisms driving cold water accumulation in Shasta Lake. It is imperative that Shasta Dam operators know which factors determine cold water accumulation in order to optimize TCD operation to maximize cold water storage. This study assesses the factors which drive cold water accumulation in Shasta Lake by examining time series data of inflow and outflow volumes, reservoir temperature profiles, river inflow temperatures, and regional meteorological data.

2. Methods

2.1. Data Compilation

[5] The development and analysis of long-term time series records for Shasta Dam included the compilation of a 52-year daily data record (1948–1999) for the following parameters: air temperature, tributary inflow, tributary temperature, regional meteorology, Shasta Dam operations, and intermittent reservoir temperature profiles. Regional air temperatures, obtained from the National Oceanographic and Atmospheric Administration National Climatic Data Center's Web site (http://www.ncdc.noaa.gov/), were collected for four stations: Burney, McCloud, Redding, and Shasta Dam. These stations were chosen based on their widespread positions within the watershed, proximity to Shasta Lake, and the completeness of the available data. These data provided an index of overall climatic trends in the region and important regional descriptors for modeling tributary temperatures. Average monthly solar radiation values for the Shasta Lake region were obtained from Smithsonian Meteorological Tables [*Beard and Willey*, 1972] and fit to a fourth-order polynomial equation. Monthly values for the Pacific Decadal Oscillation (PDO) index were obtained from the Joint Institute for the Study of the Atmosphere and Oceans, University of Washington (http://tao.atmos.washington.edu/data_sets/). The El Niño-Southern Oscillation (ENSO) was characterized by monthly values for the Multivariate ENSO Index (MEI), provided by the Climate Diagnostics Center, National Oceanic and Atmospheric Administration Web site (http://www.cdc.noaa.gov/~kew/MEI/).

[6] Tributary inflows are recorded at U.S. Geological Survey gauging stations located near each of the three main reservoir inflows (the upper Sacramento River, the McCloud River, and the Pit River). Temperature models were developed to simulate inflow temperatures for the three main tributaries to Shasta Lake using the 10 years (1989–1999) of available daily river temperature data for these sites. While a variety of parameters were utilized during model development, air temperature, solar radiation, and time of year provided the best fits for these data. These temperature models used piecewise multiple regression techniques [*Salas et al.*, 1980; *Neter et al.*, 1996] to remove a strongly cyclical residual error by developing separate regression models for approximately monthly increments. That is, a separate multiple regression model was developed for each month in each tributary. We applied these inflow temperature models to all years assessed in our study so that any estimation error/bias from this model was distributed evenly between prebypass and bypass years.

2.2. Cold Water Volume Estimates

[7] The BOR's Central Valley Operations Office maintains records of Shasta Dam's daily operations and local meteorology. Daily reservoir operation data include surface elevation, reservoir volume, and total outflow volume. Outflow volume, subdivided based on discharge elevation, was categorized as power generation, spillway release, and upper, middle, and lower outlet releases. BOR personnel have taken biweekly temperature profiles of Shasta Lake on a semiregular basis since 1944, including several long periods of intensive sampling resulting in a nearly complete data set of the reservoir's thermal characteristics for the years 1960–1974 and 1989–1999. Reservoir thermal profiles were consistently taken at 7.6-m intervals (the original sampling interval was 25 feet) from 191 m (above mean sea level) to the surface, at a location within 122 m of the outlet structure. Temperature profiles were linearly interpolated between the 7.6-m intervals, at a 0.76-m interval scale. The volume of cold water in Shasta Lake on a given sampling day was derived using thermal profiles, a hypsographic curve, and averaging the volumes of water below and above 8.3°C to calculate a mass of water with an average temperature of 8.3°C. For example, if Shasta Lake had a bottom layer of cold water with an average temperature and volume of 8.0°C and 1 km^3, respectively, overlain by another layer with an average temperature of 8.9 and a volume of 0.5 km^3, the combined "mixed" temperature and volume of these two layers would be 8.3°C and 1.5 km^3.

2.3. Principal Components Analysis (PCA) Time Series Analysis

[8] The use of PCA for analyzing interannual variability in time series was first proposed by *Craddock* [1965] and is described in detail by *Jassby* [1999]. Here we apply it to the

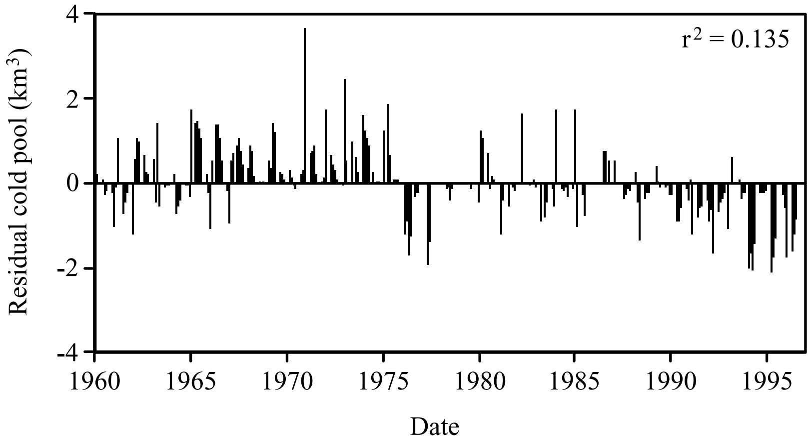

Figure 1. Time series plot of residual cold water volume in Shasta Lake. The residual cold water volume was calculated by subtracting the long-term average cold water volume for a specific time of the year from the actual cold water volume for a specific date. Cold water volume was determined by averaging the volume of water below and above 8.3°C to calculate the total mass of water with an average temperature of 8.3°C. The long-term trend in cold water residuals is highly significant (F test = 57.33, $P < 0.0001$).

cold water time series. This unique application of PCA decomposes time series with a higher than annual frequency into seasonal "modes" of variability, each of which is characterized by its own time series. By isolating the modes contributing to interannual variability, the underlying mechanisms become easier to identify and less likely to obscure each other as in more traditional approaches. The method reveals the number of independent modes of variability, the time of year in which they are most important (represented by the component coefficients), and their relative strength from one year to the next (represented by the amplitude time series, or ATS). These features often provide strong constraints on and clues for the identity of the underlying mechanisms. When analyzing a monthly time series, such as the cold water storage series, an n by p data matrix is first formed in which each of the p = 12 columns represents a specific month for the n years of record. Principal components (PCs) were estimated by singular value decomposition of the covariance matrix of the data matrix. The number of significant PCs must be chosen because if at least two significant PCs are found, the subset of significant PCs must be rotated [*Richman*, 1986]. We used the scree test, in which all PCs up to and including the first major inflection point in the cumulative variance plot are considered significant [*Cattell*, 1966]. We retained the significant PCs and rotated them using the varimax algorithm [*Richman*, 1986], calculating the new component coefficients and ATS. The ATS can then be explored for their relations to other explanatory variables in an effort to explain the seasonal variation in the original time series.

2.4. Linear Modeling

[9] We examined the relationship between cold water accumulation and possible predictor variables using linear models. The relatively small number of years and the multiplicity of potential predictor variables preclude use of more complicated models. In constructing multivariate models for ATS 1 and ATS 2, we considered the following general predictor variables: reservoir volume, inflows and outflows, and Shasta dam air temperatures for the corresponding modes of variability, as well as August–September hypolimnetic bypass volume. We also considered fall reservoir water temperatures and winter cold water supplies, respectively, when developing multivariate regression models for ATS 1 and ATS 2. We selected the best subset of possible predictors on the basis of Mallows C_p statistic [*Mallows*, 1973], one of several approaches for choosing predictor variables that minimize prediction error [*Jassby*, 1999]. We chose the model with the lowest C_p, with the additional constraint that all predictor values had to be statistically significant ($P < 0.05$).

3. Results

[10] In order to analyze interannual variability for cold water volume, we first eliminated the average annual cycle, calculated by taking monthly averages for 1960–1974 and 1989–1999. The residuals exhibit a striking pattern (Figure 1): Prior to 1989 the residuals about the average annual cycle were mostly positive, while after 1989, when hypolimnetic bypass operations were in effect, residuals were mostly negative.

[11] The PCA time series decomposition allowed identification of distinct processes affecting year-to-year variability in the monthly time series of cold water volume. Figure 2 shows the different modes detected and their corresponding variance, along with the cumulative variance for all modes. In the scree test, all modes up to and including the first major inflection point in the cumulative variance plot were considered significant [*Cattell*, 1966]. In Figure 2 the first two modes described 88% of the year-to-year variability. The first mode (Figure 3a) explained 64% of the variability alone and was strongest from February through July. The second mode (Figure 3b) explained an additional 24% of the variance and was strongest during December and January. The resulting ATS, showing how the modes varied over the length of the time series, are given in Figures 3c and 3d. The first mode was generally positive from 1960 to 1974 and negative from 1989 to 1996 (Figure 3c). The second mode was positive throughout most of the 1960s, negative

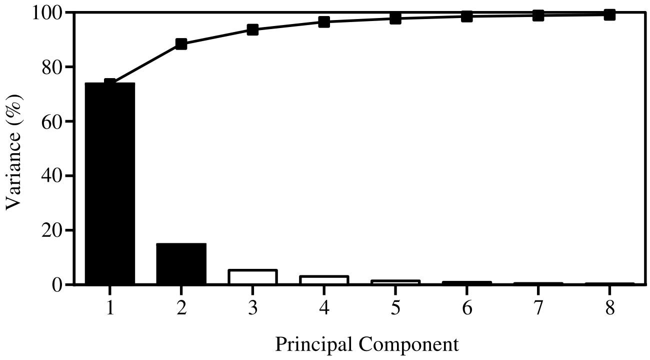

Figure 2. A scree plot of variances obtained from the rotated PCA. Only principal components (modes) 1 and 2 were statistically significant at the P = 0.05 level as determined by Monte Carlo simulations. Solid line indicates cumulative variance.

from 1968 to 1974, and mostly positive from 1989 to 1996 (Figure 3d).

[12] The last step in this time series decomposition was to assess the variation in the ATS with explanatory variables during this same time period. In order to make this analysis more intuitive, the actual data values of cold water volume were used in place of the ATS. This is possible because the two modes overlap very little and the two series are therefore highly correlated with the average dynamics of the most important months in the respective modes. As we are primarily interested in the factors that influence cold water accumulation in Shasta Lake, and cold water inputs usually end by early April, we examined average cold water volumes during the months of February to April. The variables considered for these multivariate models and their individual correlations with February–April and December–January cold water volumes are given in Table 1.

[13] The late summer/fall hypolimnetic discharges (i.e., low-level bypass) and spring air temperatures accounted for 76% of the variability in ATS 1, while winter air temperatures at Shasta Dam, winter inflows to Shasta Lake, and fall reservoir temperatures accounted for 68% of the variability in ATS 2 (Table 2). The multivariate model developed for ATS 1 was well behaved. Two predictor variables were statistically significant at the 0.01 or better level (Table 2), and the partial residual plots also support this model (Figure 4). However, it should be noted that 1993 had the highest residual error in both Figures 4a and 4b.

[14] To place these statistical results in perspective, we can convert each of the coefficients obtained to actual predicted changes in cold water accumulation during the bypass period by multiplying the appropriate coefficient by the respective mean difference for a given parameter between the prebypass and bypass years. For example, the average fall residual reservoir temperature during the prebypass period was $-0.63°C$ and the average fall residual temperature during the bypass period was 0.98°C, for a mean difference of 1.61°C. As the fall temperature coefficient was -0.253, the multivariate model for ATS 2 predicts that Shasta Lake accumulated 0.41 km^3 (1 km^3 = 0.81 $\times$ 10^6 acre feet) less cold water (i.e., 1.61°C $\times$ -0.253 km^3/°C = -0.41 km^3) during the winter following bypass years due to warmer fall water temperatures.

[15] We can use the average differences between nonbypass and bypass years as well as the coefficients reported in Table 2 (as was done for the example above) to calculate how differences in reservoir operation and climate lead to reduced cold water accumulation during the bypass years. If we start sequentially, we find that during the years 1991–1996 BOR dam operators bypassed on average 1.28 km^3 cold water during the late summer/fall period. (Shasta Lake has a total volume of 5.6 km^3). The volume of hypolimnetic water discharged in late summer/fall was strongly correlated

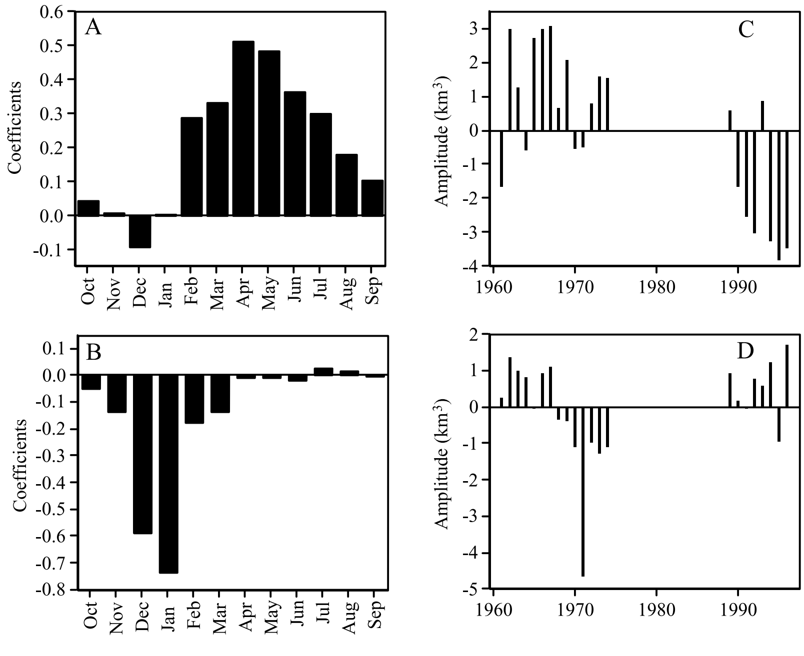

Figure 3. Annual modes of variability for (a) mode 1 and (b) mode 2 with (c and d) their respective amplitude time series.

Table 1. A Matrix of Simple Regression Coefficients (r^2) Between Measures of Seasonal Cold Water Storage and Various Predictor Variables for Shasta Lake

Variable	Dec.–Jan. Cold Pool	Feb.–April Cold Pool	Time Lag, days
ATS1	0.06	0.84	
ATS2	0.92	0.10	
Bypass	0.18	0.66	
Volume	0.11	0.23	0, 0
Inflow	0.36	0.04	8, 0
Outflow	0.43	0.00	3, 0
Air temperature	0.33	0.53	13, 30
Pacific Decadal Oscillation	0.16	0.40	0, 0
El Niño-Southern Oscillation	0.04	0.15	0, 0
Oct./Nov. reservoir temperatures	0.25	...	
Dec.–Jan. cold pool	...	0.26	

with fall reservoir water temperatures (r^2 = 0.66) because these hypolimnetic discharges removed almost all of the coldest water from Shasta Lake, which effectively warmed the entire reservoir. During the winter following bypass years, Shasta Lake accumulated 0.41 km^3 less cold water due to warmer fall reservoir temperatures. Furthermore, Shasta Lake winter air temperatures were on average 0.68°C warmer during the bypass years, which should have according to our multivariate model for ATS 2 resulted in approximately 0.18 km^3 less cold water accumulating. The recent bypass period 1989–1996 had on average 0.66 km^3 less total winter inflows, which according to our multivariate model should have resulted in approximately 0.21 km^3 less cold water accumulating during the bypass years. Because hypolimnetic bypasses warm the reservoir and because Shasta Lake is experiencing a trend of warmer winter air temperatures, BOR dam operators can expect Shasta Lake to accumulate approximately 0.67 km^3 less cold water in the future (relative to long-term averages) during the winter period.

[16] The PCA time series decomposition suggests winter (December–January) and early spring (February–April) cold water accumulation are in large part independent (r^2 = 0.26). Early spring cold water accumulation will therefore have a much greater impact than winter accumulation on cold water availability during the critical late summer/fall period. Early spring cold water accumulation was most strongly related to the previous fall's bypass volumes (Figure 4a), which on average resulted in 0.89 km^3 less cold water accumulation during the following spring compared to prebypass years. Cold water accumulation was also related to spring air temperatures (Figure 4b). As recent bypass years were on average 1.0°C warmer during the spring than the prebypass years, this amounted to 0.37 km^3 less cold water. These results are consistent with the general result that the bypass years had on average 1.56 km^3 less cold water during the months of February–April.

[17] To further explore the strong correlations between fall hypolimnetic bypasses and spring cold water accumulation, we correlated the magnitude of the fall bypasses against Shasta Lake cold water volumes in each successive month (Figure 5). This plot shows fall hypolimnetic bypasses correlated moderately strongly with fall cold water storage, weakly with winter cold water storage, and moderately strongly with the succeeding spring's cold water storage. While this pattern is perplexing, the management implications of this association are clear. According to the coefficient presented in Table 2, approximately 0.89 km^3 less cold water will accumulate in Shasta Lake during springs following late summer/fall hypolimnetic discharges averaging 1.04 km^3. This quantity is 25% of the mean annual cold water storage (3.53 km^3) in Shasta Lake prior to these hypolimnetic bypasses.

[18] Calculations comparing the volume of hydrologic inputs and their temperatures to cold water accumulation in Shasta Lake showed net cold water inflows on average accounted for only 38% of total cold water accumulation in

Table 2. The Statistical Results of the Multivariate Models for ATS 1 and ATS 2, As Well As Mean Comparisons for the Prebypass and Bypass Years[a]

Variable	Coefficient	*t*-Test	Probability	Multivariate Model Fit (r^2)	Prebypass Mean, ±1 SD	Bypass Mean, ±1 SD	Difference	*t*-Test	Probability	Coefficient × Difference, km^3
				February-April (ATS 1)						
				0.79	3.47 ± 0.37	1.97 ± 0.88	−1.56	3.77	0.0012	
Intercept	3.324									
Fall bypass	−0.855	4.01	0.0008		0 ± 0	1.04 ± 0.57	1.04	3.72	0.0014	−0.89
Spring air temperatures	−0.372	2.74	0.0135		−0.33 ± 0.87	0.66 ± 0.77	0.99	2.71	0.0135	−0.37
Spring volume	0.264	1.72	0.1029		0.22 ± 0.23	−0.64 ± 0.96	−0.86	2.23	0.0377	−0.23
Sum										−1.48
Error (RMS)										±0.48
				December–January (ATS 2)						
				0.68	1.37 ± 0.80	0.69 ± 0.43	−0.68	2.60	0.0171	
Intercept	0.887									
Winter air temperatures	−0.264	3.43	0.0030		−0.62 ± 1.24	0.06 ± 1.49	0.68	1.07	0.2961	−0.18
Winter inflows	0.322	2.81	0.0117		0.65 ± 1.04	−0.01 ± 0.64	−0.66	1.83	0.0820	−0.21
Oct./Nov. reservoir temperatures	−0.253	2.23	0.0387		−0.63 ± 0.40	0.98 ± 0.73	1.61	4.51	0.0002	−0.41
Sum										−0.80
Error (RMS)										±0.48

[a]The units of the ATS cold water volumes, fall bypass, spring volume, and winter inflows are cubic kilometers for the relevant time period. The units for all temperature results are degrees Celsius. The ATS 1, ATS 2, and bypass volumes are actual values; all other results are residuals from long-term mean annual trends.

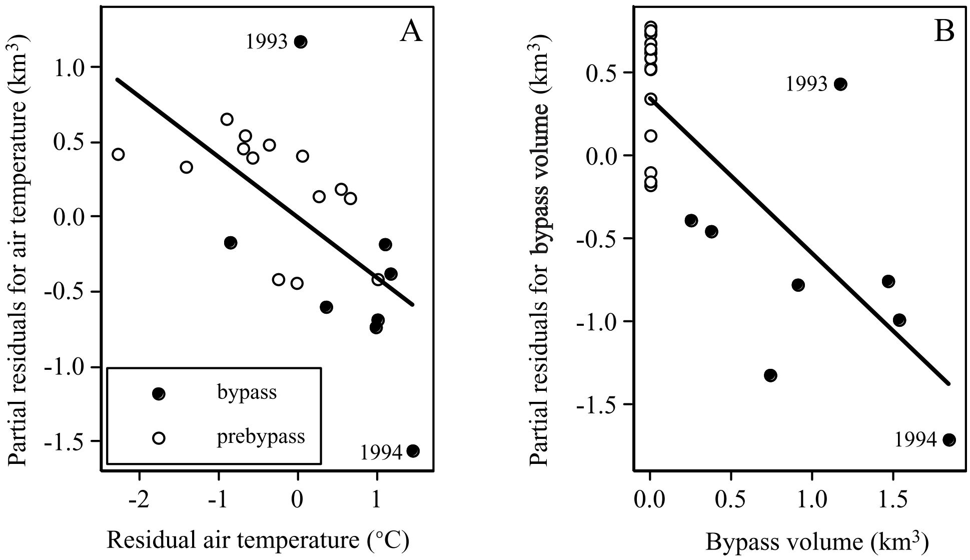

Figure 4. Residual plots for the air temperature and bypass volume terms of the multivariate model for ATS 1 using data from the prebypass and bypass periods.

Shasta Lake during January [*Nickel*, 2000]. This result suggests air-water heat exchange (or reservoir cooling) accounted for on average 62% of cold water accumulation during January. During January the Shasta Lake region typically experiences its coldest air temperatures and the water column mixes down to an average depth of 50 m. It is likely that the timing between cool air temperature and deep mixing has a very important impact on how the reservoir accumulates cold water during the winter. Figure 6 shows that maximum deep winter mixing during bypass years occurs approximately 3 weeks earlier (mid to late December) than in prebypass years. During prebypass years the maximum deep winter mixing occurred near mid-January, when air temperatures are typically at their lowest.

[19] We also considered what we thought would be the simplest model of cold water accumulation to Shasta Lake, i.e., cold water accumulation as a simple function of the inflow rate and temperature, without finding any clear trends. An index of inflow and temperature impacts on Shasta Lake cold water accumulation was calculated by taking the predicted river temperature and subtracting 8.3°C (to derive warming or cooling inflows) and multiplying this residual temperature by the river inflows at any given time. Other reference temperatures besides 8.3°C were also tried. Despite the simplicity of this input approach, it gave a much weaker fit to actual cold water dynamics than did models based on processes occurring in the reservoir itself.

[20] January air temperatures have increased significantly over the length of this time series (Figure 7). Thus, if the cold water accumulation during this same time period is being driven by air temperature, which is suggested by our multivariate analysis of PCA ATS 2, this increase could be one of the main factors driving the reduction in winter cold water storage during the bypass period. This trend also suggests winter warming may continue into the future. The Shasta Dam air temperature annual cycle is shown in Figure 8, with horizontal lines depicting the 8°–9°C temperature range. The air temperature cycle falls below this bar during the months of December and January, further suggesting that air temperature drives additional cold water accumulation. However, as Figure 7 shows, the present January air temperature may not follow the annual cycle depicted in Figure 8. According to Figure 7, January air temperatures may currently be almost 1°C higher than depicted in Figure 8.

4. Discussion

[21] Understanding the mechanisms driving interannual variation in cold water accumulation in Shasta Lake will make it easier to optimize reservoir operations to maximize cold water storage. A refinement of reservoir management could lead to increased spawning habitat for endangered chinook salmon during late summer and early fall. This is important for several reasons. First, our time series analysis suggests less cold water may be available for salmon conservation in the future due to direct and indirect impacts of late summer/fall hypolimnetic discharges on cold water accumulation in Shasta Lake. Second, regional climatic trends suggest Shasta Lake might experience less winter cooling and greater spring warming in the future. Third, the BOR is proposing to reduce water diversions from Trinity

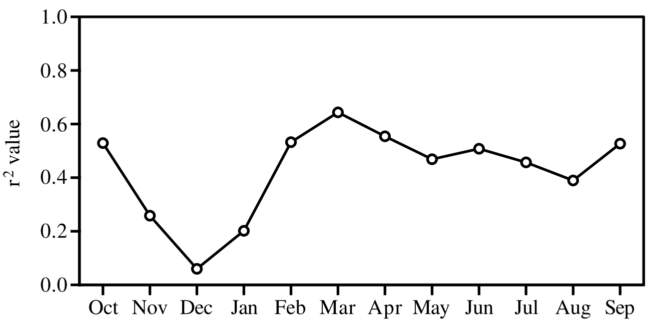

Figure 5. The cross correlation between fall hypolimnetic bypass volumes and Shasta Lake cold water storage in successive months.

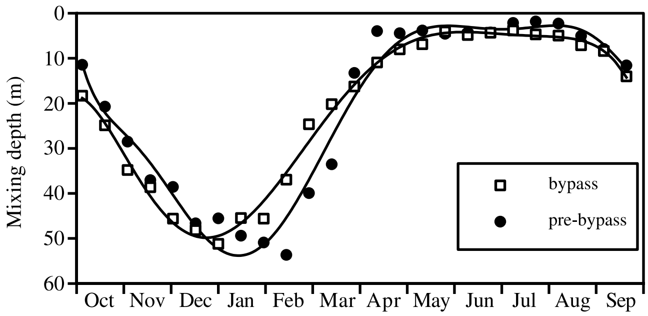

Figure 6. Changes in the mixing regime during prebypass and postbypass years. Mixing depth was calculated as the depth at which the water temperature differs by 1°C from the near-surface temperature (i.e., 0.5 m depth).

Reservoir (Claire Engle Lake) to the Sacramento River in order to maintain minimum flow requirements in the Trinity River for endangered steelhead trout (*Oncorhynchus mykiss*). For the years 1995–2000, an average of 0.62 ± 0.15 (±1 standard deviation) km^3 was diverted from the Trinity system (via Whiskeytown Reservoir) during the hot summer period of July to mid-October. If less water is diverted from the Trinity system, this shortfall will have to be met from Shasta Lake, which will further tax Shasta Lake's ability to meet cold water delivery objectives in the critical late summer/fall period.

[22] The PCA showed that there were two major components to the cold water cycle that acted independently. Together, these modes (February–April and December–January) described 88% of the variation in the overall time series. If these two periods act independently, as the PCA indicates, it would be difficult to achieve a good fit using one statistical model for the entire year. In fact, we initially attempted this approach and achieved a poor overall fit (r^2 = 0.29). One factor related to reservoir operation (hypolimnetic bypasses) and one related to climate (spring air temperatures) explained the majority of the first mode (ATS 1), which characterized variability in February–April cold water volumes. A multiple regression model for the second mode (ATS 2) suggests that fall reservoir water temperatures, winter inflows, and winter air temperatures drive most of the cold water accumulation during December–January. However, since the two PCA modes are orthogonal and cold water storage in the months of December–January and February–April are only weakly correlated, these results also suggest that factors influencing cold water accumulation during the months of February–April will overall have a much greater impact on cold water accumulation in Shasta Lake. One could plausibly argue these statistical results justify ignoring the factors regulating cold water accumulation during the midwinter. In fact, adding a term describing the December–January cold water volumes to the multivariate model for ATS 1 did not improve its overall fit.

[23] *Hanna* [1999] and *Hanna et al.* [1999] used the hydrodynamic water quality model CE-QUAL-W2 to conclude downstream temperature objectives were more likely to be met if the reservoir elevation was maximized for as long as possible during the winter and spring. Although not included in the final multivariate model obtained for ATS 1 (because it failed to meet our $P < 0.05$ criteria), our statistical analysis provided some evidence that reservoir volume could impact cold water accumulation (t test = 1.72, $P = 0.10$). Because Shasta Lake volume is controlled during the spring in accordance with flood protection rule curves, overall variability in February–April reservoir volume was only ±12% (±1 standard deviation) of overall reservoir volume. This modest variability in February–April volume may have made it difficult to detect a strong association with cold water accumulation using a regression approach. The coefficient for spring volume versus cold water accumulation regression suggests that on average 26% of any additional volume maintained in Shasta Lake would be manifest as additional cold water. However, it should be noted that in some years, maximizing Shasta Lake volume is not possible due to high water demands and/or the need for flood protection during "wet" years.

[24] Another alternative, as discussed by *Hanna* [1999], would be to relax the downstream temperature objective during early summer in an effort to preserve more cold water for the late summer and early fall (the primary spawning time for winter-run chinook salmon). This alternative may make it easier to maintain the optimal 100-km spawning reach throughout the summer and fall. Ideally, an optimization scheme should be developed to allocate Shasta Lake cold water supplies to the times of the year when they will have the greatest benefit for endangered and economically important salmonids.

[25] Our multiple regression model results for ATS 2 suggest cold water storage can be optimized at the beginning of the year (January) by raising the reservoir level to the maximum allowable elevation. This strategy would take advantage of lake mixing when local meteorological conditions are optimal for cooling. Lakes which are subjected to intense wind mixing during cool winter temperatures will have lower overall temperatures [*Farmer and Carmack*, 1982]. As soon as average air temperatures rise above 9°C (the upper target release temperature), attempts should be made to promote thermal stratification in Shasta Lake. This would help minimize the surface warming evident in our multiple regression model of ATS 1. This type of scenario (deep winter mixing followed by a rapid change to thermal stratification) was prevalent in the prebypass years (Figure 6), when cold water accumulation was greatest. The change in

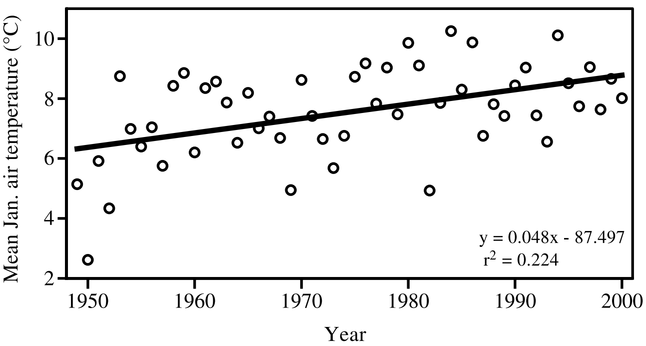

Figure 7. Average January air temperatures at Shasta Dam (1949–2000). The long-term trend in Shasta Lake January air temperatures is statistically significant (F test = 14.41, $P < 0.0004$).

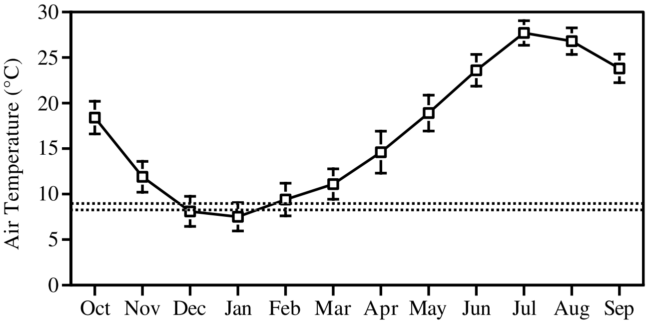

Figure 8. Average annual air temperature cycle at Shasta Dam. Horizontal lines identify the 8°–9°C range. The confidence intervals represent ±1 standard deviation.

outflow strategies has apparently altered the mixing dynamics of Shasta Lake, shifting the period of maximum deep winter mixing 3 weeks earlier, which is offset from the coldest January air temperatures.

[26] To optimize cold water accumulation, deep mixing should be promoted via releases as close to the surface as practical from mid-December to late January. This time period coincides with declining air temperatures and, most important, cooler average air temperatures than reservoir surface temperatures. As air temperatures begin to seasonally increase at Shasta Lake, we recommend switching to an operating scenario designed to facilitate thermal stratification in order to provide an insulating surface water layer to protect any previously accumulated cold water from surface warming. According to our data, 5 February is the average date when the annual cycle of Shasta Dam air temperature surpasses 9°C (Figure 8). Studies performed on Wellington Reservoir in Australia suggest metalimnetic withdrawals promote thermal stratification [*Fischer et al.*, 1979; *Imberger and Patterson*, 1990]. Withdrawing water at the thermocline depth intensifies the density difference between the epilimnion and hypolimnion, promoting stronger thermal stratification. During the late winter/early spring period in Shasta Lake, when strong thermal stratification has still not set up, we recommend releasing water from the metalimnetic thermocline, i.e., ~10–15 m below the reservoir surface. However, additional investigation needs to be performed on strategies for promoting thermal stratification because Wellington Reservoir is not only located in a different climatic region, but it is also much smaller (maximum depth = 30 m) than Shasta Lake and thus may exhibit quite different thermal characteristics. Flood releases should be made from the epilimnion during the midwinter and from the metalimnion during late winter and early spring. These flood releases should never be made from the hypolimnion (low-level releases) because this will deplete Shasta Lake of its coldest water. However, low-level flood releases are already avoided in order to control turbidity downstream of the reservoir.

[27] In contrast to the relation between bypass volume and fall reservoir water temperatures, the correlation between spring cold water accumulation and the previous late summer/fall's hypolimnetic discharges is perplexing. This is especially the case since this is the strongest correlation observed in this study and it is strong for the following fall and spring, but weak during the winter (Figure 5). Hypolimnetic releases appear to cause Shasta Lake to accumulate approximately 0.9 km^3 less cold water in the following spring. Regardless of the mechanism behind this correlation, Shasta Lake typically accumulates less cold water during winter and springs following late summer/falls with large hypolimnetic discharges. The multiple regression model presented in Table 2 suggests this is due not simply to the bypass years being unusually warm and dry, although this was a contributing factor. Our result which shows that years with large hypolimnetic discharges are characterized by poor cold water accumulation during the following winter/spring is in contrast to *Hanna et al.*'s [1999] finding using the CE-QUAL-W2 model that hypolimnetic discharges do not influence reservoir temperatures in successive years.

[28] Similar to the results of several studies of large lakes [*McCormick and Fahnenstiel*, 1999; *George et al.*, 2000; *Livingstone and Dokulil*, 2001; *Livingstone*, 2003], our study of Shasta Lake showed air temperature anomalies had a strong impact on interannual water temperature fluctuations. In a detailed analysis of long-term temperature fluctuations in Lake Washington (United States), *Arhonditsis et al.* [2004] found Lake Washington water temperatures were strongly correlated with air temperature anomalies and that due to recent warming in the Seattle, Washington, region, Lake Washington water temperatures have exhibited a strong warming trend during the last 40 years. *Arhonditsis et al.* [2004] also found epilimnetic warming in Lake Washington was much more intense than hypolimnetic warming (i.e., 0.45° and 0.19°C per decade, respectively) and that warming was especially intense in the surface layer during the summer stratified period (0.63°C per decade). Both our study of Shasta Lake and Arhonditsis et al.'s study of Lake Washington found the El Niño-Southern Oscillation (ENSO) was only weakly correlated with the reservoir/lake temperature fluctuations. *Arhonditsis et al.* [2004] found both spring/summer and fall/winter temperature fluctuations in Lake Washington were moderately strongly correlated with the Pacific Decadal Oscillation (PDO) [*Mantua and Hare*, 2002], whereas we found only the Shasta Lake February–April cold water volume was moderately strongly correlated with the PDO. In further contrast to the results of Arhonditsis et al., our multiple regression models did not include the PDO as a significant term, whereas the PDO was a significant component of both the spring/summer and fall/winter lake temperature models for Lake Washington [*Arhonditsis et al.*, 2004]. It is notable, however, that both the Shasta Lake and Lake Washington analyses indicated the PDO has much stronger associations with lake/reservoir water temperature fluctuations than does the ENSO.

[29] The strong relation between cold water accumulation and winter and spring air temperatures is worrisome because there already appears to be a significant warming trend in winter air temperatures at Shasta Lake (Figure 7) and because it is well established that the world's climate is warming [*Huang et al.*, 2000]. According to the results of our multiple regression model, Shasta Lake will accumulate 0.64 km^3 less cold water in the future for each 1°C increase in mean winter/spring air temperatures.

[30] A warmer climate could also result in reduced snowpack accumulation, causing cold water inputs to Shasta Lake to occur during a shorter period of time

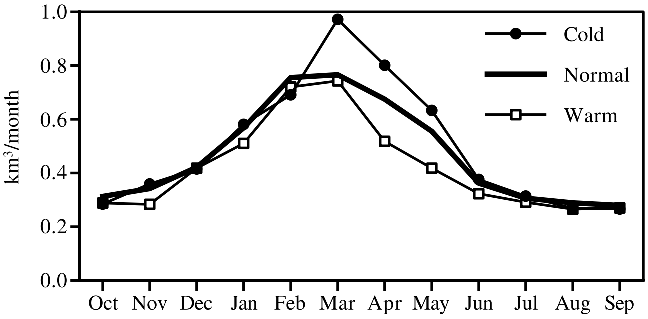

Figure 9. Median monthly hydrologic inputs to Shasta Lake during warm, normal, and cold years. Warm conditions were represented by the 12 warmest years in the 50-year record (approximately the upper quartile), normal conditions were represented by the intermediate 26 years (approximately the second and third quartiles), and cold conditions were represented by the 12 coldest years (approximately the lower quartile). The warmest years were on average 1.3°C warmer than the coldest years. Typical monthly inputs were represented by the median monthly hydrologic inflow rate for the three groupings. The differences in warm and cold year inflows to Shasta Lake were statistically significant as determined by a two tailed t-test during the months of March and April ($P < 0.05$) and marginally significant during May ($P < 0.10$) but are not significantly different any other months.

[*Hamlet and Lettenmaier*, 1999], which could also make it more difficult to store this cold water for the late summer period since Shasta Lake has a relatively short effective retention time of 0.69 ± 0.16 years (i.e., mean annual inputs/mean annual volume). To examine how long-term climate change might impact hydrologic inputs to Shasta Lake, we used the 50-year database assembled for this study to compare monthly hydrologic input rates during warm and cold annual quartiles for this database. Figure 9 shows that during warm years Shasta Lake had smaller hydrologic inflows during the months of March, April, and May. Since inputs to Shasta Lake are usually below 8.3°C during March, these results suggest Shasta Lake is likely to receive less water and less cold water if climatic warming trends continue as projected. The combination of increased warming of the reservoir itself, as well as reduced and warmer inflows, suggests climatic warming could pose a serious threat to the long-term prospects for winter-run chinook salmon survival downstream of Shasta Lake.

[31] We found that all cold water accumulates in Shasta Lake by mid-April, which provides 4 months for the responsible agencies (i.e., BOR, California Department of Fish and Game (CDFG), NMFS, U.S. Fish and Wildlife Service (USFWS), etc.) to plan for the critical late summer/fall period. Thus, by midspring, Shasta Dam operators can determine exactly how much cold water will be available the remainder of the year. Given this information it should be possible to develop a series of scenarios given a representative range of future conditions. The main factor influencing change in cold water availability by late summer/fall will be summer temperatures in the Central Valley and their impact on the ability of the BOR to meet downstream temperature and agricultural and urban water demands. BOR dam operators can use past water demands during cold, average, and warm summer conditions in the Central Valley to predict cold water supply at the end of summer for a range of conditions given known initial conditions (i.e., the beginning of May cold water supply). The scenarios developed should be designed to maximize the river area with suitable spawning habitat without exposing any of this habitat to excessively warm water before critical temperature sensitive salmon life history stages (i.e., eggs in redds, and fry in the river) have fully developed. One of the most risky operating strategies is to have an overly optimistic projection for late summer cold water supplies and to ultimately run out of cold water before the temperature-sensitive life history stages have been completed. Because Shasta Lake is thermally stratified during the late summer, running out of cold water can result in a sudden increase in downstream temperatures. This is important because a big mistake for a short time period in meeting downstream temperature objectives will have a greater impact on fish mortality than a smaller mistake for a longer period of time [*Kilgour et al.*, 1985]. Our results clearly show cold water delivery schemes based on prebypass conditions will be overly optimistic. During the last decade with bypass scenarios, far less cold water has accumulated in Shasta Lake than typically occurred prior to 1990.

[32] Because of the population growth, recent droughts, climatic warming, and increasing demands to maintain habitat for threatened or endangered fish, conflicts between demands for water and how water resources are managed are becoming increasingly prevalent in the western United States [*Adams and Cho*, 1998; *Schmidt et al.*, 1998]. There are several important parallels between our study of Shasta Lake and the ongoing Upper Klamath Lake controversy [*Cooperman and Markle*, 2003; *Levy*, 2003; *Lewis*, 2003]. These include the fact that the BOR manages both systems, climate change may be warming the water of both systems, threatened and endangered fish are involved, and the demands on water supplies in both the Shasta Lake and Klamath Lake systems are likely to increase in the future. However, these systems are also very different. The BOR has much greater control over water retention in Shasta Lake because it has an 8 times larger volume, it is much deeper, and its relative storage can be varied much more than is the case for Klamath Lake. Because Klamath Lake is very shallow (mean depth 2.6 m), it only has an epilimnion and is therefore not capable of storing large volumes of cold hypolimnetic water like Shasta Lake does.

5. Conclusions

[33] Our analyses suggest Shasta Lake has two modes (December–January and February–April) of variability in cold water accumulation, the latter of which is the most important. February–April cold water accumulation is strongly correlated with a combination of the preceding late summer/fall hypolimnetic discharges and spring air temperatures. The bypass years of 1989–1996 had poor cold water accumulation due to direct impacts of the hypolimnetic bypasses, reduced winter inflows, and warmer air temperatures during the winter and spring. Late summer/fall hypolimnetic releases led to Shasta Lake accumulating approximately 0.9 km^3 less cold water in the following

spring. On the basis of the weak correlation ($P = 0.10$) between spring cold water accumulation and reservoir volume, increasing the volume of Shasta Lake by the currently proposed 6.5% will only slightly alleviate cold water shortages in the future. However, having a greater reservoir volume should improve operational flexibility for Shasta Lake, which might improve this system's capacity to deliver cold water in the future. Since almost all cold water inflow and accumulation in Shasta Lake occurs before May, resource managers will have several months to plan cold water utilization and salmon spawning habitat management during critical periods of the year. Because our statistical analyses suggest atmospheric heat exchange has a strong impact on Shasta Lake cold water accumulation, we recommend that Shasta Lake be managed to promote water column mixing during midwinter and thermal stratification during late winter and spring.

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